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The Accuracy of School Classifications for the 2002 Accountability Cycle of the Kentucky Commonwealth Accountability Testing System

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THE ACCURACY OF SCHOOL CLASSIFICATIONS FOR THE 2002 ACCOUNTABILITY CYCLE OF THE KENTUCKY COMMONWEALTH ACCOUNTABILITY TESTING SYSTEM

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THE ACCURACY OF SCHOOL CLASSIFICATIONS FOR THE 2002 ACCOUNTABILITY CYCLE OF THE KENTUCKY COMMONWEALTH ACCOUNTABILITY TESTING SYSTEM

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Introduction

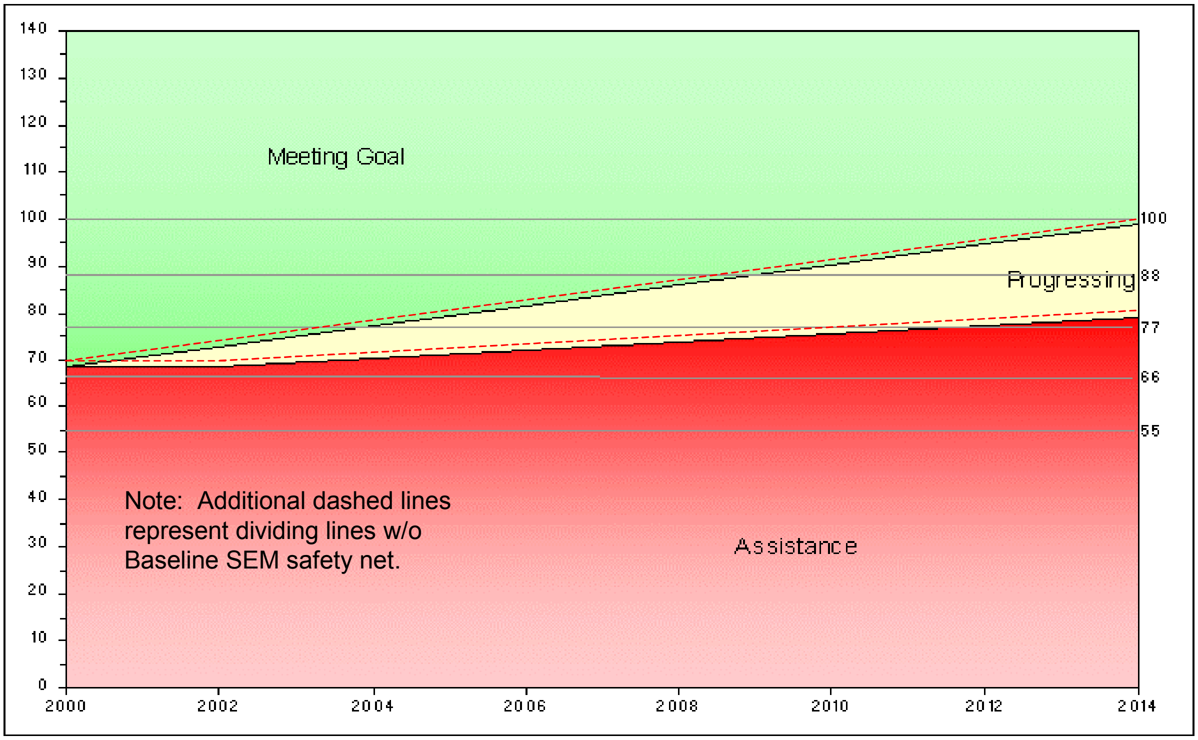
Kentucky's Commonwealth Accountability Testing System (CATS) was implemented in 1999 as a modification of the Kentucky Instructional Results Information System (KIRIS). Beginning with KIRIS, public schools in Kentucky have been classified by their successes in educating students. Both the KIRIS and CATS systems have significant consequences tied to schools' classifications, making the accuracy of these classifications an important issue. Hoffman and Wise (2001) reported the accuracy of these classifications for the interim accountability cycle that bridged KIRIS and CATS. The present report presents the method used for calculating classification accuracy and the results for the first of the CATS long-term accountability cycles that are legislated to occur every two years beginning in 2002 and ending in 2014.

The report begins with an overview of the CATS long-term accountability model and then presents classification accuracy results for the first accountability cycle. Details of how the results were obtained then follow. Although the results are reasonably straightforward, computational details are complex and are mainly presented for technical readers.

CATS Long-term Accountability Model

The CATS long-term accountability cycle began with the 1998-99 school year, which was the first year in which the newly revised Kentucky Core Content Test (KCCT) was administered. Because CATS testing occurs each spring, we reference each year with the spring date only. Data from 1999 and 2000 constituted the "baseline" years upon which target scores for the period through 2014 have been set for every Kentucky school. These targets will be used to place schools into one of three categories: *Meeting Goal*, *Progressing*, and *Assistance*.

For each school, a School Growth Chart (see Figure 1) is constructed to depict school performance targets from 2000 through 2014. A "goal line" is initially plotted from the point on the chart representing a school's academic index for the baseline period and ending at the point that represents an academic index of 100 in the year 2014. The ending point is the statewide goal for all schools in 2014. The line is then adjusted downward to incorporate an allowance for measurement error. That is, the beginning of the line is actually plotted at one standard error of measurement (SEM) below the school's calculated index and ends at one SEM below 100. The SEM refers to measurement error in the baseline accountability index.



Note: (Edited from a randomly selected school from the KDE website
http://www.kde.state.ky.us/oaa/implement/School_Report_Card/)

Figure 1. Modified School Growth Chart

Every school in Kentucky has a School Growth Chart indicating its prescribed trajectory, but the chart in Figure 1 has been modified from the ones presented to the schools by showing a goal line *without* measurement error allowance. At the end of every two-year accountability cycle, a school's new accountability index is compared to the solid line that divides the Meeting Goal (medium shaded or green if viewed electronically) area from the Progressing area (lighter shaded or yellow if viewed electronically). If the new Index score is at or above the line, then the school is improving close enough to the true-target rate (the dashed line) to be labeled Meeting Goal.

Figure 1 also shows two additional lines on the chart that divide Progressing and Assistance (darker shaded or red) areas. As defined by Kentucky regulation, the Assistance line begins with the baseline academic index at 2000, is sketched horizontally over to the year 2002 and is then extended to the point at the year 2014 representing an accountability index of 80. Like the goal line, the Assistance line used for actual classification is adjusted downward by one SEM. Again, the dashed line in Figure 1 (which is not presented to schools) shows the true line. The solid line that includes the safety net and divides the Progressing and Assistance areas in the chart is used to classify schools.

The distinction between the solid lines plotted on the chart with the built-in safety net and the dashed lines without the safety net is important for later classification accuracy computations. Throughout this report, we will refer to the “safety net” line and the “true” line to maintain this distinction.

Figure 1 is not the complete story for school classification. In addition to the accountability index scores, two additional criteria are applied before a school can receive rewards for meeting its goal or be required to engage in special actions if it does not. These criteria include meeting goals for (a) reducing the proportion of Novice students in the school and (b) staying within maximum limits on the number of dropouts. At this time, neither of these criteria is considered in this analysis of school classification accuracy.

School Classification Accuracy Results

No assessment system is perfect, which means that an observed score, such as a school accountability index, is the product of two factors: true standing and measurement error. Although observed scores are known, true scores are not because the exact error in any given score is uncertain. Test reliability statistics, however, allow the estimation of how errors are distributed, making it possible to address the following two questions:

- What is the probability that a school is classified accurately? That is, given a school’s observed baseline and end-of-cycle accountability index scores, what are the odds that its true scores would result in the school being placed in the same accountability classification as the one assigned?
- What is the probability that a school is incorrectly classified? That is, what are the odds that a school’s true scores would result in the school being placed in a different accountability classification from the one assigned?

Table 1 presents a summary of classification accuracy results. The columns indicate school classifications considering only their accountability index scores. Ignored are special criteria concerning reduction in percentages of students classified as Novice and limits on school dropouts. *Italicized numbers* represent percentages of all students, so that their sum is 100% (within rounding). The ***bold italicized numbers*** represent the percent of schools expected to have true scores in a range that would yield the same accountability classification as the assigned classification. Thus, 34% of all schools were assigned “Meeting Goal” and are expected to have true classifications of “Meeting Goal.” Another 36% of all schools were assigned “Progressing” and are expected to have true classifications of “Progressing.” Finally, 7% of all schools are assigned Assistance and are expected to have true classifications of “Assistance.” The sum of the bold percentages, 77%, is the percentage of all schools whose true classifications are expected to match their assigned classifications. That is, school classification accuracy, for the system as implemented, is 77%.

Table 1
Classification Probabilities for 2002 School Accountability

Expected True Category	Assigned Category (Before Novice and Drop Criteria Applied)			Total Expected for True Classifications
	Meeting Goal	Progressing	Assistance	
Meeting Goal	***34%***	*1%*	*0%*	35%
Progressing	*15%*	***36%***	*1%*	53%
Assistance	*0%*	*6%*	***7%***	13%
% in Observed Class	49%	43%	8%	100%
Number in Obs Class	567	491	87	1145

Notes: Bold italics numbers indicate expected probabilities of accurate classifications. They sum to 77%. Only schools with data for all four years and with constant grade configurations are included in the analysis.

The bottom two rows of Table 1 show the percent of schools and total number with accountability index scores in each observed classification. In the right-most column, the table shows the percent of schools that would be expected in each classification if their true scores were knowable. Notice that more schools are actually assigned to the Meeting Goal category than are expected from our projections about true scores (49% vs. 35%). Conversely, fewer schools are assigned Assistance than are expected (8% vs. 13%). Part of this difference is the result of the application of the baseline safety net: Schools just under their true Goal or Assistance line are given the “benefit of the doubt” via the SEM allowance. As a result, the system places more schools into the Meeting Goal category than expected, but limits the chances that schools are classified too low because of measurement error.

Table 2 shows how accurate the accountability system would be if schools were classified without the baseline SEM safety net. These results are perhaps a better indication of measurement accuracy. Without the safety net, schools would be assigned to the category most likely to contain their true score. Therefore, overall accuracy, at 82% (the sum of the bold percentages in Table 2), is higher without the SEM safety net than with it. While seemingly paradoxical, this result was expected. Including the baseline safety net increases the total number of schools that are classified as Meeting Goal in order to reduce the risk of erroneously underclassifying schools. The result is that some schools are overclassified.

Table 2
Classification Probabilities for 2002 School Accountability without Baseline Safety Net

Expected True Category	Observed Category Without Applying Baseline SEM Safety Net			Total Expected for True Classifications
	Meeting Goal	Progressing	Assistance	
Meeting goal	***32%***	*3%*	*0%*	35%
Progressing	*8%*	***41%***	*4%*	53%
Assistance	*0%*	*3%*	***9%***	12%
% in Observed Class	40%	47%	13%	100%
Number in Obs Class	453	543	149	1145

Notes: Bold italics numbers indicate expected probabilities of accurate classifications. They sum to 82%. Only schools with data for all four years and with constant grade configurations are included in the analysis.

Table 3 gives a more comprehensive picture by specifically identifying schools that benefited from the baseline safety net. In this table, six types of schools are identified:

1. Schools that are Meeting Goal with and without the baseline safety net (i.e., above the dashed goal line in Figure 1). These are labeled “MG & MG” in Table 3.
2. Schools that are Meeting Goal with the safety net, but are Progressing without the safety net (i.e., schools between the solid and dashed goal lines). These are labeled “MG & P” in Table 3.
3. Schools that Progressing with and without the baseline safety net for the Assistance line. These schools are below the solid goal line and above the dashed Assistance line in Figure 1 and are labeled “P & P” in Table 3.
4. Schools that are in Assistance with and without the baseline safety net (i.e., below the solid assistance line in Figure 1). These schools are labeled “A & A” (last column) in Table 3.
5. School that are Progressing with the safety net, but Assistance without the safety net (i.e., between the solid and dashed assistance lines). There schools are labeled “P & A.”
6. Two unusual schools, labeled “MG & A” in Table 3, were classified as meeting goal with the baseline safety net, but would have been classified as Assistance without it. Both of these were relatively small schools with very high baseline index scores (94.3 and 97.3) that dropped slightly for 2001/2002 (94.2 and 97.1). Without the safety net, the drop in scores places the schools in Assistance; however, the loss is not so great that it places their score below their safety net goal.

Table 3
Classification Probabilities with and without SEM Safety Net

Expected True Category	Classification with SEM Safety Net & without SEM Safety					
	MG & MG	MG & P	P & P	MG & A	P & A	A & A
Meeting Goal	**80%**	**22%**	2%	**24%**	1%	0%
Progressing	20%	77%	**90%**	32%	**47%**	13%
Assistance	0%	1%	8%	44%	52%	**87%**
% in Obs Class	100%	100%	100%	100%	100%	100%
Number in Obs Class	453	112	431	2	60	87

MG & MG = Meeting Goal with or without safety net.
MG & P = Meeting Goal with safety net but Progressing without it.
P & P = Progressing with or without safety net.
MG & A = Meeting Goal with safety net but Assistance without it.
P & A = Progressing with safety net but Assistance without it.
A & A = Assistance with or without safety net.

Table 3 shows percentages that total 100 within each column. The values express the likelihood of a given type of school having true index values that would result in a classification of Meeting Goal, Progressing, or Assistance. For example, schools above the dashed goal line (the "MG & MG" schools) have an 80% probability of being accurately classified as Meeting Goals and only a 20% probability of being truly in the Progressing category.

Comparing the "MG & P" to the "P & P" schools shows the effect of applying the safety net more explicitly. Again, the "MG & P" schools are those with index scores categorizing them as Progressing were it not for the safety net. These schools are most likely to have true scores that would place them in Progressing range (77%), but to protect the 22% that are likely to be in the true Meeting Goals range, all of these schools receive rewards. That is, in order to avoid under-classifying 22% of these schools, 78% (100%-22%) of them are overclassified. In contrast, those schools below the solid goal line and above the solid assistance line (the "P & P" schools that are progressing with or without the safety net) have a 90% chance of truly being Progressing and only a 2% chance of truly being Meeting Goal. In other words, if a school has received a classification of Progressing, the odds are high that the school's true standing, if known, would be in Progressing.

Schools in the final three columns all have scores that place them in Assistance without the safety net and in each case, the probabilities are greater for them being in Assistance than any other category. For the two unusual "MG & A" schools, however, the probability of them truly being Assistance is less than half (44%). They are more likely to be above Assistance (24+32=56%), and close enough to true Meeting Goal (24%) to be given rewards.

The "P & A" schools have a 47% chance of actually being Progressing and are granted this status by the safety net. Finally, the "A & A" schools (Assistance by both classifications) have an 87% probability of being accurately classified. That is, for the schools that were classified as needing Assistance, chances are high that the classification is accurate.

Note that the safety net had to be set prior to the availability of complete data for 1999 through 2002 and was chosen to be one SEM in the baseline accountability index. The actual error is a function of measurement error in both baseline and end-of-cycle scores. The data in Table 3, therefore, indicate how well the safety net actually protected schools from being misclassified. It seems to have functioned quite well in protecting individual schools from underclassifications by measurement error.

These adjusted assignments may not be the best way to view the state learning progress as a whole. The safety net assignments indicate that 50% of schools are meeting their accountability goals. On the other hand, the expected true distributions (last column in Table 1 or 2) indicate that, if measurement error were removed, only about 35% of the schools meet the intended growth targets. A better estimate of state-wide school improvement is provided by the proportion of schools which would have been classified as Meeting Goal without the safety net factor (40%, according to Table 2).

Technical Details for Calculating School Classification Accuracy

The material that follows is technical in nature because of the large number of steps involved in reaching the results. This section is written for the technical audience. Some of the steps are straightforward. Other steps require the technical reader to think in some unusual ways. Much of this complexity is created by the need to consider the set of Kentucky schools not as a single population (which is normally the case when considering test statistics), but as representing multiple populations with measurement characteristics that differ by school size and by school grade configuration. An additional complication is that schools were classified based on index differences from both Goal line projections and Assistance line projections. The presentation begins with an overview of the procedure and then unfolds with details of the computations.

Overview

Student-level Kentucky Core Content Test scores are used to compute school accountability index scores. These tests are administered to selected grades such that all assessments are administered in typical elementary, middle, and high schools. Eight assessments are components of the KCCT and are prepared for Kentucky to assess achievement.[1] The eight assessments are augmented by a national norm-referenced test, the CTBS/5. Table 4 indicates the grades in which the assessments are administered. Kentucky Core Content Tests are indicated by subject.

Table 4
Assessments by Grade Level

Subject	Grade									
	3	4	5	6	7	8	9	10	11	12
Arts & Humanities			X			X			X	
Mathematics			X			X			X	
Practical Living/Vocational Studies			X			X		X		
Reading		X			X			X		
Science		X			X				X	
Social Studies			X			X			X	
On-demand Writing Prompt		X			X					X
Writing Portfolios		X			X					X
CTBS/5	X			X			X			

For each KCCT, students are classified into one of four achievement levels: Novice, Apprentice, Proficient, and Distinguished. The lower two levels, Novice and Apprentice, are subdivided into three sublevels (low, middle, and high) for the four primary content disciplines (Reading, Mathematics, Science, and Social Studies). The point values used to calculate

[1] As defined by the Kentucky Core Content Assessment and laid out by the Kentucky Core Content Test Blueprint (**http://www.kde.state.ky.us/oaa/valid/blueprint.asp**).

schools' average student achievement for primary content areas are shown in Table 5 and other areas in Table 6.

Table 5
Achievement Levels and Point Values for Mathematics, Reading, Science, and Social Studies

Achievement Level		Point Value
Distinguished		140
Proficient		100
Apprentice	High	80
	Middle	60
	Low	40
Novice	High	26
	Middle	13
	Low	0

Table 6
Achievement Levels and Point Values for Arts & Humanities, Practical Living/Vocational Studies, and Writing

Achievement Level		Point Value
Distinguished		140
Proficient		100
Apprentice		60
Novice	Attempt	13
	No attempt	0

CTBS/5 scores are included in the school accountability formula by converting percentiles to a scale similar to that for the KCCT. Specifically, students' quartiles (lowest to highest) are converted to scores of 0, 60, 100, and 140, and these scores are used to compute schools' average CTBS/5 scores.

In addition to the KCCT and CTBS/5 data, schools also receive scores for a composite of nonacademic factors such as attendance rate, retention rate, and dropout rate. Each school generates the nonacademic data.

Given this array of data, estimating school classification accuracy can be conceptualized as a two-phase process that begins with the estimation of SEMs, or error variance, for schools' accountability cycle scores and is followed by transformation of error variance into the classification accuracy probabilities that appear in Tables 1, 2, and 3.

Estimating Standard Errors of Measurement

Schools' achievements are classified for CATS based on the difference between their end-of-cycle targets and their end-of-cycle accountability indexes. Therefore, the measurement error of most interest is the error in this difference. Error in the difference, however, is a function of the error in the baseline index (which is used to compute end-of-cycle targets) and the error in the end-of-cycle index. The estimation of these errors is complicated by a variety of factors.

First, school accountability index scores, for any cycle, are a weighted composite (weighted sum) of the scores from the various assessments administered in the schools. Therefore, the SEM for each accountability index (baseline and end-of-cycle) can be computed from SEMs for each assessment used in the computation (i.e., the KCCTs, CTBS/5, and non-academic indicators). As a result, the analyses deal with three types of SEMs:

- **Assessment SEMs** for school-level scores for Grade 4 Reading, Grade 10 Reading, Grade 9 CTBS/5, etc.
- **Accountability Index SEMs** for the baseline school index and each end-of-cycle index. Accountability SEMs are a function of assessment SEMs.
- **Classification SEMs,** which indicate the measurement error in the difference between observed accountability index and the goal for any particular accountability cycle. Classification SEMs are a function of accountability SEMs.

Generalizability Theory analyses, elaborated after Yen (1997) and Miller (1999), are used to calculate assessment SEMs for all except the nonacademic indicators. The Generalizability analyses are identical to those used in calculating classification accuracy for the interim accountability model. Two Generalizability models were used: one for KCCTs with different forms in a given year and one for assessments in which all students had the same form. Details of these analyses are presented in Hoffman and Wise (2000b and 2001) and are repeated in the Technical Appendix of this report. In general, the model considers student scores as data points (in lieu of test items) but it is complicated by the fact that school scores for any end-of-cycle assessment are derived from different students for the two years in the cycle with these students taking multiple forms of the assessments that also differ across years. In other words, each student is like a test item, providing a single measure of the instructional capacity of the school. The test item analogy, however, is complicated by the two-year measurement period and by the potential for differences in test forms to impact how students function as a yardstick of school capacity. Variations in students, forms, and years can signal potential sources of measurement error. Further discussion is provided in the Appendix.

No method existed for estimating the error variance for the nonacademic scores, so when computing classification accuracies for the interim accountability model Hoffman and Wise (2001) explored using the SEM values based on an assumed reliability of 1 (perfect reliability) and values based on an assumed reliability of 0 (total unreliability). It was determined that the estimate of overall school error was only slightly different for these two extreme assumptions. Therefore, we selected a conservative reliability estimate (.7) for the non-academic scores to use in calculations of school classification accuracy.

The second factor considered in estimating measurement error is the amount of data available for a particular school. Other things being equal, with more data there is less error. As a result of this principle, we expected large schools to be measured more accurately than small schools because their index scores are based on more students. Therefore, analyses of assessment SEMs were conducted on three representative school sizes: the lower third, the middle third, and the upper third.

These considerations mean that for any given cycle there are 81 assessment SEMs estimated by the Generalizability analyses: the 27 grade-by-assessment content areas (listed in Table 4) times the 3 school sizes.

A third consideration when estimating SEM is the fact that not all schools fit the typical elementary, middle, and high school model. In fact, accountability index SEMs had to be calculated for schools with 14 different grade configurations. (The exact combinations are presented later in Table A-6 in the Appendix.) Fortunately, accountability index SEMs are computed from the separate grade/subject assessment SEM. Therefore, calculating accountability SEMs for schools with any particular grade configuration means including assessment SEMs for the assessments administered in the grades included in that configuration.

A fourth consideration is the requirement to estimate SEMs for a broad range of school sizes. In order to increase the precision of assessment SEM estimates for schools that do not fall in the representative sizes, an interpolation procedure was required to generate assessment SEM estimates for schools with anywhere from 10 to 500 students per grade.

Finally, schools were classified according to how their end-of-cycle accountability index fell in relation to their goal and assistance line targets for that cycle. Therefore, measurement error in the baseline and the end-of-cycle indexes were jointly considered. Computing classification accuracy involves consideration of the differences between a school's actual end-of-cycle index and the values specified by that school's true goal and assistance lines, i.e., when the lines are unadjusted by the baseline safety net. Carefully notice that schools will actually be classified according to where their accountability index falls in relation to the goal and assistance lines as plotted to include allowance for measurement error. For purposes of determining classification accuracy, however, schools' end-of-cycle accountability indexes must be compared to goal and assistance lines that are not adjusted for the potential error. In a sense, the classification accuracy analysis determines the extent to which the error allowance is protecting schools from inappropriately low classifications.

Note on multiple SEMs

Because of the complexity of the analysis process with its multiple levels of SEMs (assessment, accountability, and classification), it is easy to lose sight of the fact that within each of these levels, multiple SEMs are computed for varying school sizes and grade configurations. This is much more complex than calculating SEMs for a typical "test" in which one given set of observations (e.g., test items) in the assessment is the same for all subjects. In the case of school assessment, the number of observations in the assessment procedure depends on the number of grades in a school and the number of students within those grades. As a result, every school size and grade configuration combination has a specific set of assessment SEMs. Likewise, every school size and grade configuration combination has a specific accountability SEM. Finally, classification SEMs depend on school size in the baseline year, school size at the end-of-the cycle, and school configuration. Our classification SEM computations allow school size to change. On the other hand, a change in grade configuration invokes special regulations, typically involving the use of district-level scores. Therefore, our classification SEM computations exclude schools that change grade configurations.

Estimating Classification Accuracy Probabilities

Standard errors of measurement indicate expected variations of observed scores given a particular true score. Schools, however, have only their observed scores and are interested in how their true score might vary from their observed score. Our method for calculating classification accuracy is based on obtaining estimates of the distribution of true scores around observed scores. In our analyses of student classification accuracy (Hoffman and Wise, 2000a) and interim accountability classification accuracy (Hoffman and Wise, 2001), we applied Bayes' Theorem and estimates of true score distributions to transform SEMs into estimates of the distribution of true scores around varying levels of observed scores.

Figure 2 illustrates the steps. First, classification SEMs are used to construct a matrix of the probabilities of observed scores given various possible true differences. The figure illustrates that these calculations are made for score intervals spreading from 0 in increments of .5 for possible true scores and observed scores. Using estimates of the probabilities of the various true scores, the top matrix in Figure 2 is converted to the bottom matrix of probabilities of various true score given potential observed scores. These operations are conducted twice: Once for differences around the goal line and once for differences around the assistance line.

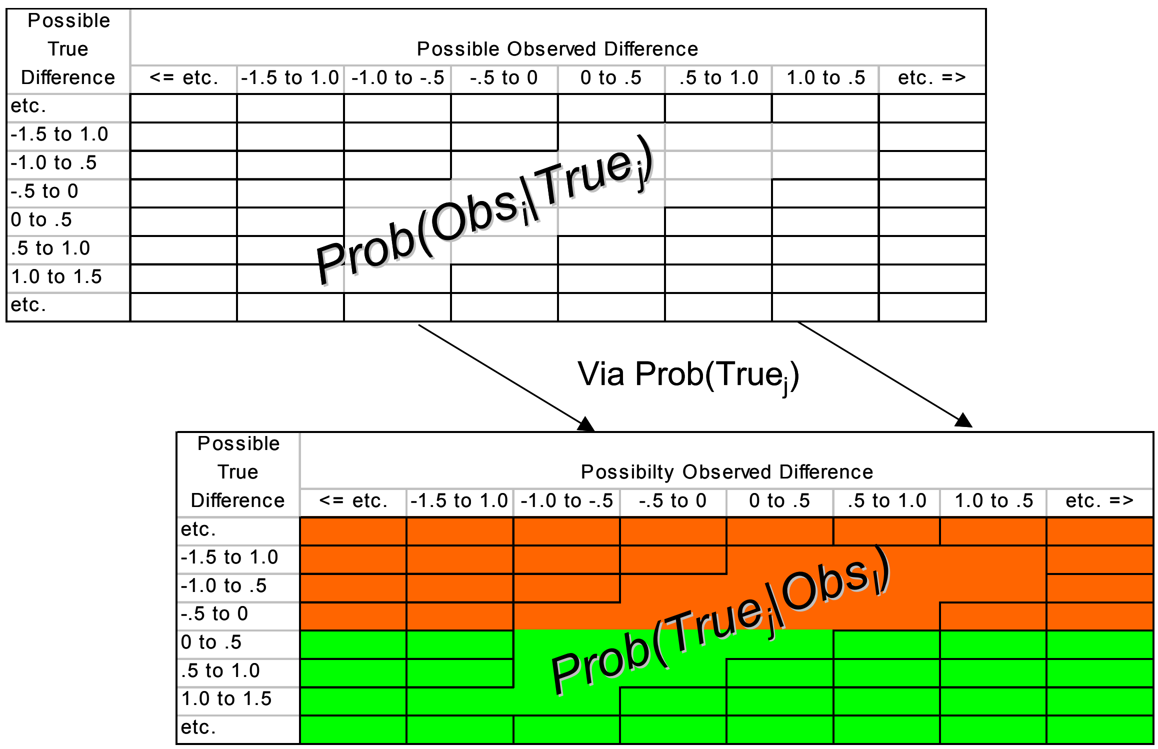


Figure 2. Schematic representation of matrices used in calculating classification accuracy.

Using the matrix of probabilities of true scores given observed scores, we can sum cells above and below 0 (the differently shaded areas) to estimate classification accuracy. The first step is to identify the column that contains a school's observed difference. Using the goal difference matrix, the probability of the school having a true Meeting Goal classification is the sum of the values in the identified column that are above the 0 true score. Using the assistance difference matrix, the probability of the school having a true Assistance classification is the sum of the values in the identified column that are below the 0 true score. Since each school's true classification must be in Meeting Goal (MG), Assistance (A), or Progressing (P), the probability of the school's true classification being Progressing can be calculated as:

Prob(P|Observed Index) = 1-Prob(MG|Observed Index) -Prob(A|Observed Index).

Assessment SEM Computations

Assessment SEMs are derived from Generalizability Theory analyses modified by a four-step process to consider varying school sizes:

- Identify representative target school sizes for Generalizability Theory analysis.
- Create synthetic schools with target sizes.
- Compute Generalizability Theory error estimates.
- Interpolate assessment SEMs for school sizes 10 to 500 per grade.

Each is discussed in detail below.

Identifying Target School Sizes

The number of students within a school will affect the reliability of school-level scores; therefore, we begin assessment SEM computations using three representative school sizes. Because schools also differ in the number of grades they contain, and because the analysis begins with grade-level data, we defined school size by the average number of students in a grade. Small schools were identified as those in the smallest one third of all schools, and the representative size was set at the median of that third, which is the 16.7th percentile of all schools. Similarly, medium schools were those in the middle one third and were represented by the 50th percentile of all schools. Finally, large schools were the largest onethird and were represented by the 83.3rd percentile of all schools.

The selection of representative school sizes was slightly complicated by the requirement to analyze data from different grades for two different years. That is, either the grade-level size for 1999 or 2000, or an average, could define school percentiles. Representative size was also affected by test form configuration. The KCCT is divided into multiple forms and we needed each form to be represented by an equal number of students in our analyses. Therefore, target sizes had to be adjusted to the nearest multiple of 12, which is the number of Arts & Humanities and Practical Living/Vocational Studies forms. By using 12 as the multiple, we also accommodated the 6 forms for the other subject areas.

Table 7 below shows the distribution of school size by grade and year, as computed for the KCCT during analyses of interim accountability classification accuracy. School sizes during the interim accountability cycle were the same as during the initial two years of the long-term accountability cycle. Therefore, school size targets determined for the interim classification accuracy analyses are usable for the present analysis. For reference, school sizes at the medians and the boundaries of the one-third size divisions are indicated, along with the maximum school size. Although there are 14 grade configurations for which accountability SEMs are calculated, schools with Grade 4 always include Grade 5, schools with Grade 7 always include Grade 8, and Grades 10, 11, and 12 are always combined. Hence, school size targets were set for Grade 4 and 5, Grade 7 and 8, and High School for the Kentucky Core Content Test. High School targets were set using only population data for Grade 10 and 11. We used these same school size targets when calculating end-of-cycle assessment SEMs because (1) school populations were not expected to shift sufficiently within the need to target a multiple of 12, and (2) an interpolation procedure was applied to cover the range of school sizes

Table 7
Identification of Representative School Sizes for Kentucky Core Content Tests

Grade	Year	School Sizes by Percentile					
		16.7th	33.3rd	50th	66.7th	88.3rd	Maximun
4	1999	30	45	59	75	96	246
4	2000	29	47	61	76	96	255
5	1999	28	44	57	73	89	290
5	2000	30	46	59	75	94	291
Grade 4/5 targets		**24**		**60**		**180**	
7	1999	35	70	126	191	246	438
7	2000	36	67	127	190	259	459
8	1999	36	71	133	191	256	430
8	2000	36	70	126	194	247	423
Grade 7/8 targets		**36**		**120**		**240**	
10	1999	61	115	179	228	298	624
10	2000	63	119	173	222	292	644
11	1999	65	110	164	202	258	563
11	2000	65	110	163	206	261	518
High School target		**60**		**168**		**240**	

Table 8 presents targets for CTBS/5 grades derived the same way as described above.

Table 8
Identification of Representative School Sizes for CTBS/5

Grade	Year	School Sizes by Percentile					
		16.7^{th}	33.3rd	50th	66.7th	88.3rd	Maximun
3	1999	31	47	63	79	105	275
3	2000	31	46	62	80	106	254
Grade 3 targets		**24**		**60**		**96**	
6	1999	25	40	59	98	222	449
6	2000	25	40	59	101	228	383
Grade 6 targets		**24**		**60**		**180**	
9	1999	33	103	173	244	356	643
9	2000	61	113	194	249	365	590
Grade 9 targets		**60**		**168**		**240**	

Selecting Eligible Schools

Given that there are not schools with exactly the target number of students nor with an equal representation of forms, we created synthetic schools to match the targets. This was done by randomly eliminating students from candidate schools. Because small-, medium-, and large-size schools have characteristics other than size that may affect measurement accuracy (e.g., smaller schools may be more homogeneous), only schools near the target size were considered eligible for the analyses. Certainly, schools could be no smaller than the target size. Selection of the maximum size eligible for the analysis was a trial and error process. In each case, we tried to balance having enough schools for stable Generalizability results without having the maximum size being subjectively larger than the target size. This was most difficult to achieve for the small middle and high schools. Random selection of students was conducted independently for every grade, subject, and school size combination. Table 9 indicates the ranges of school sizes (target to maximum) that became candidates. The numbers of schools that met each criterion and were used in the Generalizability Theory analysis are presented later.

Table 9
Ranges of candidate school sizes

	Small		Medium		Large	
Grade	Target Size	Max. Size	Target Size	Max. Size	Target Size	Max. Size
3	24	36	60	72	96	120
4	24	36	60	78	96	120
5	24	36	60	78	96	120
6	24	36	60	84	180	240
7	36	60	120	170	240	360
8	36	60	120	170	240	360
9	60	120	168	240	240	643
10	60	120	168	240	240	643
11	60	120	168	240	240	643
12	60	120	168	240	240	643

Estimating Assessment SEMs using Generalizability Theory

After creating synthetic schools at the target student populations, assessment SEMs were calculated using the Generalizability models specified by Hoffman and Wise (2000b, 2001) and repeated in the Appendix. Results for baseline years appear in Table A-4 and the 2002 end-of-cycle results are in Table A-5. The assessment SEMs required for computation of accountability index SEMs are the square roots of the Generalizability Theory absolute error variance estimates. Absolute error was chosen because schools must meet fixed standards. Relative error is inappropriate because making comparisons to other schools does not play a role in classifying schools. Tables A-4 and A-5 also provide other Generalizability results, including relative error variance, total variance, and absolute and relative Generalizability coefficients. The Generalizability coefficients estimate the reliabilities of the school mean test scores for each assessment included in CATS. In general, these reliabilities are in the mid-eighties to mid-nineties and are higher for larger schools than for smaller schools.

To estimate error variance for the non-academic component of the accountability index, total variance across schools (separately for elementary, middle, and high schools) was calculated and multiplied by 1 minus our assumed reliability of .7. The square root of that result yielded our estimate of non-academic SEM. The same non-academic SEM is used for all school sizes, because normal measurement theory may not apply. That is, large schools may have a more difficult time getting accurate data about each of their students than small schools. In turn, that may counteract the general measurement principle that more data decreases measurement error.

Interpolating Assessment SEMs for School Sizes 10 to 500

In the previous step, assessment SEMs were produced for representative school sizes. In order to increase the precision of the SEMs for schools with student populations at other than the representative sizes, an interpolation procedure was used for each grade/assessment combination. This procedure estimated SEMs for school sizes between 10 and 500 by weighting the distance between any given school size and the representative sizes. More specifically, for each assessment the procedure began with the Generalizability absolute error estimates for the three representative school sizes (small, medium, and large), then:

- For each grade-level (g), assessment (a), and representative size (r), within-school, student-level, error standard deviation (SESD) was estimated from the school-level Generalizability Theory absolute error (AERR), number of forms for the assessment (NF), and number of persons per form (NP) for the representative school size (where NF times NP is representative school size = NRS) and the formula relating variance of means (school scores in this case) to variance of observations (students in this case):

$$SESD_{gar} = \sqrt{AERR_{gar} \times NRS_{gar}} \tag{1}$$

- Interpolate within-school error standard deviations for alternate school sizes (or $SESD_{gan}$, where n stands for an alternate size), where s, m, and l refer to small, medium, and large representative sizes, respectively:

If $n \le NRS_s$, let $SESD_{gan} = SESD_{gas}$ (2)

If $NRS_s < n < NRS_m$, let (3)

$$SESD_{gan} = \left(\left(n - NRS_s\right) \times SESD_{gam} + \left(NRS_m - n\right) \times SESD_{gas} \right) \div \left(NRS_m - NRS_s\right)$$

If $NRS_m \le n < NRS_l$, let (4)

$$SESD_{gan} = \left(\left(n - NRS_m\right) \times SESD_{gal} + \left(NRS_l - n\right) \times SESD_{gam} \right) \div \left(NRS_l - NRS_m\right)$$

If $n \ge NRS_l$, let $SESD_{gan} = SESD_{gal}$ (5)

- Finally, student-level error standard was used to project back to school-level error standard depending on school size:

$$AssessmentSEM_{gan} = SESD_{gan} \div \sqrt{n}\,. \tag{6}$$

The results of these interpolations was an array of 491 SEMs for each of the 27 grade/subject assessments, including on-demand writing, writing portfolio, and CTBS/5 for both the baseline years and the end-of-cycle years. Note that not all school sizes are expected to be present among Kentucky schools. In a sense, these estimates are "what if" values, with estimates available for any size from 10 to 500 based on the assumptions that (1) schools near the representative sizes are similar in student error variance, and (2) interpolation between sizes follows common assumptions about variances of means (for schools) given variances in the subjects (students) making up the means.

Accountability Index SEMs Computations

A school's accountability index for the baseline years or for the end of any of the long-term cycles is a two-year weighted average of the assessment scores available for the grades contained within the school. Consequently, SEM in the accountability index can also be computed by appropriately weighting and summing assessment SEMs.

The general formula for calculating the variance of a weighted composite from the separate variances of the individual components of the composite is:

$$\sigma^2_{Composite} = \sum_{i=1}^{n} w_i^2 \sigma_i^2 + 2\sum_{i=1}^{n}\sum_{j=1}^{n} r_{ij} w_i w_j \sigma_i \sigma_j \tag{7}$$

A composite can be decomposed into its true and error components such that some of the variance terms refer to true score variance and some to error variance. Errors are assumed to be uncorrelated with each other or with true scores, so second term components drop out with respect to error variance terms (i.e., when $r_{ij} = 0$). The resulting formula for an accountability SEM becomes:

$$AccountabilitySEM_{sc} = \sqrt{\sum w_{ac}^2 \; SEM_{as}^2}\;, \tag{8}$$

for any given combination of school size (*s*) and configuration (*c*), where the summation is over all assessments (*a*). Table A-6 in the Technical Appendix presents the assessment weights. Note that, except for the K-to-12 configuration, some assessment weights are 0.

With 14 grade configurations and 491 school sizes, 6,784 accountability SEMs were computed for the baseline years and another 6,784 accountability SEMs were computed for the end-of-cycle years. As expected, SEMs vary by both the average number of students in a grade and the number of grades in a school. They range from approximately .5 for schools with large total populations to approximately 2.5 for schools with small total populations. Note that these SEMs are "theoretical." There are not 6,784 schools in Kentucky, so most of the size-by-configuration cells in the matrix are not applicable to any particular school. Like the assessment SEMs, these accountability SEMs are "what if" values applicable given the same assumptions indicated for the assessment SEMs.

Classification SEM Computations

The above procedures provide "look-up" tables for the various grade-configuration-by-school-size combinations for 1999/2000 and for 2001/2000 accountability SEMs. The next step is the computation of classification SEMs using the tabled values. At this point in the procedure, computational process requirements exceed the "what if" approach used for assessment and accountability SEMs. There are simply too many potential combinations of classification difference scores and accountability SEMs to create look-up tables, particularly since schools may have changed sizes between the baseline and end-of-cycle years.[2] Therefore, each school in the analysis is treated individually in the computation of classification SEMs.

True Target Indexes

Classification SEMs are a weighted function of the error variance in the baseline accountability index and error variance in the end-of-cycle accountability index where the weighting is based on the weighting used to calculate the classification index (i.e., the difference between end-of-cycle index and target). In order to calculate the classification SEM, the formula for the true target classification index is needed. Note that the true target index is not shown on the School Growth Chart or used to classify schools. On the other hand, SEM is a statistic about true scores. Therefore, the true target computations are required. Once again, there are two computations, one for the Goal line and one for the Assistance line. In addition, computation of the true target indexes themselves will be required in a later step of the overall process for calculating classification accuracy.

True Goal Target

The true Goal target lies on the line connecting the baseline index (BI) in the year 2000 to the constant value of 100 in 2014. The slope of the line is:

$$Goalslope = (100 - BI) \div (2014 - 2000). \tag{9}$$

Therefore, the true Goal target at the end of any cycle, where cycles (C) begins with Cycle 1 in 2002 is:

$$TG_c = BI + 2C((100 - BI) \div 14) = BI(1 - (2C \div 14)) + (200 \div 14)C, \tag{10}$$

which can be interpreted as a weighted function of the baseline accountability index plus a constant.

True Assistance Target

The Assistance target for Cycle 1 ending in 2002 is simply the baseline index. For cycles 2 through 7, the true Assistance line begins at the value of the baseline index plotted at 2002 and ends at 80 in 2014. The slope of this line is:

$$Asstslope = (80 - BI) \div (2014 - 2002). \tag{11}$$

Therefore, the true Assistance target at the end of any cycle, where cycles (C) begin with Cycle 2 in 2004 is:

$$TA_c = BI + 2(C-1)((80 - BI) \div 12) = BI(1 - (2(C-1) \div 12)) + (160 \div 12)(C-1), \tag{12}$$

that can also be interpreted as a weighted function of the baseline accountability index plus a constant.

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[2] If schools change configurations, special index computation rules apply, frequently involving use of district-level scores. These types of schools have been excluded.

Classification and Classification SEM

Ignoring for the moment the baseline safety net, school classification is based on the difference between a school's targets (Goal and Assistance) and its obtained scores:

- Positive differences from the Goal target indicate membership in the Meeting Goal category.
- Negative differences from the Assistance target indicate membership in the Assistance category.
- Negative differences from the Goal target coupled with positive differences from the Assistance target indicate membership in the Progressing category.

Calculation of classification SEMs requires only straightforward application of the formula for variance of a weighted composite, recognizing that the error variance terms are assumed to be uncorrelated. Therefore, classification accuracy for Meeting Goal versus the two lower categories is a function of error variance in the difference between TG_c and the end-of-cycle index (AI_c):

$$ClassificationSEM_G = \sqrt{SEM_{AI}^2 + \left(1 - \left(2C \div 14\right)\right)^2 \times SEM_{BI}^2}\ , \tag{13}$$

where references to school size and configuration for SEMs are assumed, but not shown, and the subscript *G* refers to errors of measurement around the Goal line.

In 2014 (the seventh cycle) the target for all schools is fixed at 100 and the weight for the error term reduces to 0. Error in the index goal decreases from its initial level in 2002 until it is 0 in 2014.

Classification accuracy for Assistance versus the upper categories is a function of error variance in the difference between TA_c and the end-of-cycle Index (AI_c). Under the rules for computing the Assistance target, in Cycle 1 the target equals the baseline accountability index. Therefore, the classification SEMs can be estimated as:

$$ClassificationSEM_A = \sqrt{SEM_{AI}^2 + SEM_{BI}^2}\ , \tag{14}$$

where reference to school size and configuration for SEMs are assumed, but not shown, and the subscript *A* refers to errors measurement associated with application of the Assistance line.

For the remaining cycles, the computation incorporates a weight on the baseline error term:

$$ClassificationSEM_A = \sqrt{SEM_{AI}^2 + \left(1 - \left(2\left(C-1\right) \div 12\right)\right)^2 \times SEM_{BI}^2}\ , \tag{15}$$

where references to school size and configuration for SEMs are assumed, but not shown, and the subscript *A* refers to errors of measurement associated with application of the Assistance line.

Note that, in 2014 (the seventh cycle) the Assistance target for all schools is fixed at 80 and the weight of the Assistance error term reduces to 0.

Shift from Standard Error to Probability Matrices

At this point, for each school eligible for the analysis, we have computed SEM for the difference scores (one for Goal and one for Assistance) used to classify schools. Standard error of measurement is an index of the likely variation of observed scores around any given true score. In other words, SEM is the expected distribution of observed scores conditional on true score. Because of the effect of size and configuration on error, difference SEMs are computed for different combinations of school size and grade configuration. The same classification SEM will be computed for all schools with the same size and configuration; however, schools with the same size and configurations cannot be expected to have the same true classification difference. While individual schools have become our vehicle for determining the set of sizes and configurations for computing classification SEMs, the SEMs produced are not particularly meaningful to the individual schools because their true classification differences are unknown. Far more useful at the individual school level is the estimate of the variation in true classification differences that is expected given any particular observed classification difference. Figure 2, presented in the overview, shows the schema for making the translation. The approach uses discrete score ranges to simplify calculations. A matrix of probabilities is created for various ranges of observed scores, given set ranges for true scores. Another matrix of probabilities for various ranges of true scores, given fixed ranges for observed scores, is then created using Bayes' Theorem and estimates of true difference probabilities.

Creating Probability Matrix of Observed Differences Given Possible True Differences

The matrices concern difference scores with 0 being the critical decision point, making 0 one of the required interval boundaries. After examining the range of differences between observed index scores and target index scores for Goal and for Assistance classification decisions, the range of differences was divided into 54 intervals. These intervals included (a) all scores less than –13, (b) all greater than +13, plus (c) the remaining 52 intervals between –13 and +13 with the width of each interval equal to .5. These same score intervals were also used for possible observed scores. For any cell in the resulting matrix, SEM values were used to calculate the probability of the identified observed difference, given the identified true difference. Calculations are based on the standard assumption that errors around any given true difference are normally distributed with standard deviation equal to the SEM.

Estimating of True Index Variance

An observed assessment score is the result of a "true" score and measurement error. Likewise, variance in observed scores is a function of variance in true scores and variance in error. Since $(SEM)^2$ is an estimate of error variance, estimates of true variance are calculated by subtracting error variance from total score variance. Since the magnitude of error variance is likely a function of school size and school configuration, we assume total variance is as well. Therefore, we investigated variance in observed classification difference scores by school size and configuration.

Calculating Total Variance in Classification Difference Scores and School Size

In order to calculate score variance, multiple observations must be available. To create these multiple observations, schools were grouped by rounding their sizes for 2001-2002 to the nearest 25 for schools up to 300. Above 300 students per grade, schools were categorized as either 350 or 450 students per grade. Variance in classification differences for both Goal and Assistance targets were calculated for each of these groups. The results are plotted in Figures 3 and 4. Each figure also displays the fit of a power function to school size. The fit is very close in both cases, as noted by the R^2 of .85 and .92 for the Goal and Assistance classification difference standard deviations, respectively. Given the strength of the relationship between size and variance in observed classification difference scores, using these size categories to estimate variance estimates is warranted. In contrast, there was no discernable pattern to the classification standard deviations for the different configurations, and several configurations contain so few schools that estimated standard deviations were either not possible or potentially unstable.

Estimating Distributions of True Differences

Having established estimates of total variance that can be applied to schools of any given size and having calculated error variance estimates for each school given its size and configuration, true variance estimates applicable for each school were calculated as the difference between the two. The next step was to use these true variance estimates to calculate probabilities of school true scores being in any of the scores intervals (-13 to +13). Computation of the array of true difference probabilities is based on the assumption of normally distributed scores centered on the mean of the differences with a standard deviation equal to the true variance estimation. True mean differences were estimated by observed mean differences, and like total variance, mean differences were estimated separately for school size category. Figures 5 and 6 show that strength of the relationship between size and mean difference as captured by second-degree polynomial equations. Again, use of school size to capture difference in means appears appropriate. Note that these true difference probability arrays are dependent on school size and configuration, but they are not yet conditioned on school observed score. That is the next step.

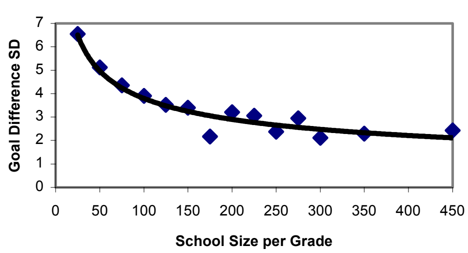

Figure 3. Classification difference standard deviations for Meeting Goal by school size.

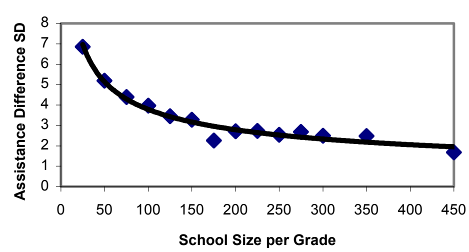

Figure 4. Classification difference standard deviations for Assistance by school size.

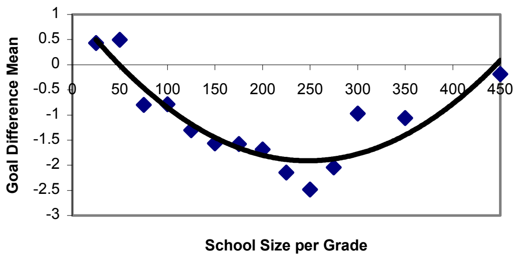

Figure 5. Classification difference means for Meeting Goal by school size.

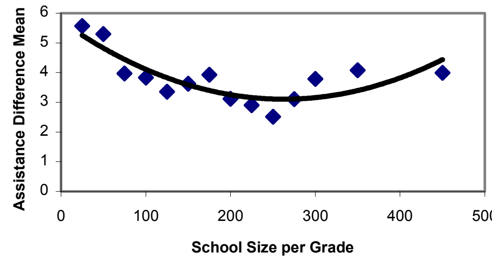

Figure 6. Classification difference means for Assistance by school size.

Creating Matrix of Probabilities of True Differences Given Observed Difference

Once again, for each school, two matrices of probabilities of observed classification differences given true differences were calculated, one for Goal decisions and one for Assistance decisions. Likewise two arrays of probabilities of true differences are created for each school. For a given observed difference the probability of classification true difference in a given interval is:

$$P(True_i|Obs_j) = \frac{P(Obs_j|True_i)P(True_i)}{P(Obs_j|True_1)P(True_1)+P(Obs_j|True_2)P(True_2)+P(Obs_j|True_3)P(True_3)+\ldots+P(Obs_j|True_k)P(True_k)}, \quad (16)$$

where Obs_j = observed difference represented by interval *j*, with *k* possible difference intervals, and $True_i$ = true difference represented by interval i, with *k* intervals represented in the probability matrix.

Bayes' transformation was applied to the data for each school. The result was a matrix of probabilities of each of the 54 true score intervals being in any of the 54 observed difference intervals, with separate matrices for Meeting Goal and for Assistance. Any given school had only one observed Goal difference and one observed Assistance difference; therefore, only one column of either school-specific Prob(True|Observed) matrix was relevant.[3] For each school, the observed column containing the school's observed difference was identified for both the Goal and Assistance matrices. Appropriate summation of cell probabilities above and below zero (described earlier) provide estimates of the probabilities of the school having a true classification in Meeting Goal and in Assistance. From these two estimates, an estimate of the probability of the school having a true classification in Progressing was computed.

Summarize Probabilities Across Schools

The final step was to summarize probabilities across school by computing mean probabilities of each of the three classifications (Meeting Goal, Progressing, and Assistance) for the observed classifications of schools (Figure 1), for the classification of schools if no safety

[3] "School-specific" is not exactly correct. All schools of a given grade configuration whose sizes were identical in the base years and in the final years will have the same probability matrix.

were applied (Figure 2), and for the joint categorization that results from considering classification with and without the safety net (Figure 3).

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Appendix
Technical Documentations

Generalizability Models

Standard errors of measure of the various components of the accountability model are estimated by Generalizability analyses of students' NAPD scores. Given that school index scores span two years, the basic model is one in which pupils are nested within forms, years, and schools, and forms are nested within years and are crossed with schools. For writing and for CTBS/5, forms are not a consideration, so the Generalizability model is reduced to one in which pupils are nested within schools and years.

Figure A-1 presents the four-facet design for the Kentucky Core Content Tests. Tables A-1, -2 and -3 presents the calculations using Brennan's (1981) notation and algorithms for generating sums of squares and variance components. For each of the grade/subject combinations, the six sources of variance in schools' two-year academic index averages include: (1) school, (2) year, (3) school by year, (4) form within year, (5) school by form within year, and (6) pupil within form within school by year. The order of the nesting terms in the last source of variance is a little ambiguous in its wording since pupils are nested within forms, within schools, and within years. However, for derivation of the error components, the expressed order of the nesting does not matter, as long as the nesting is captured.

Random, fixed, or sampled from a finite universe

Generalizability theory explicitly considers the universe in which observed scores are interpretable. Typically, the items that make up a particular test are only viewed as samples of an infinite array of similar items. Being sampled from an infinite domain, test items are typically considered "random." On the other hand, some facets may cover the intended universe to which scores are intended to generalize. Year, for example, could be considered fixed because the universe of generalization is two years and both years are sampled. On the other hand, year could be considered as sampled from a finite universe. The logic is this: The school academic index, while directly interpretable as the average of students' achievement, is being used to make inferences about the instructional programs of those schools. An accountability cycle is four years long. Changes in instruction that occur in any of those four years could impact students' achievement in the final two years. Thus, the universe of generalization could be viewed as instructional change that occurred in any of the four years of the cycle. Only two of the four years are assessed, however. Other than being illustrative of sampling within a fixed domain, we are making no strong argument that the present data be treated with years being samples of a fixed four-year domain. Instead, we are suggesting that years be considered fixed. Forms and pupils are assumed to be randomly sampled from an infinite domain. Table A-3 indicates that the value of two sources of variance (year and school x year) reduce to zero when years are considered fixed.

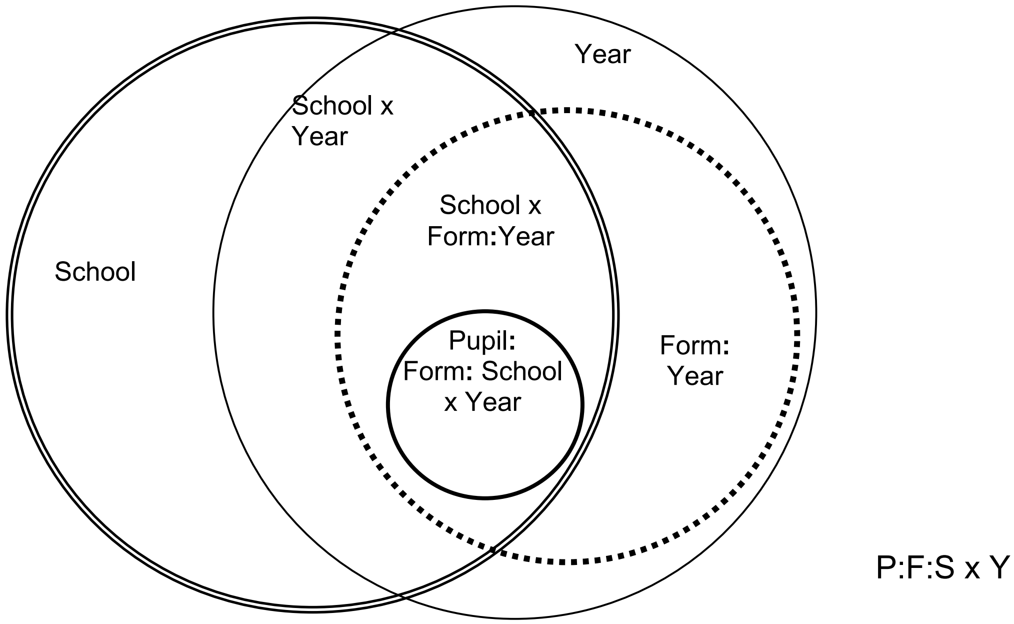

Figure A-1. Generalizability theory design representing Kentucky Core Content Test two-year accountability cycle.

Table A-1
Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – Random Effects Estimates

Effect	df	Means	SS
School (s)	n_s - 1	$\bar{X}_s = \frac{1}{n_y n_f n_p} \sum_y \sum_f \sum_p X_{syfp}$	$n_f\, n_y\, n_p\, \Sigma\, \bar{X}_s^2$ - $n_s\, n_y\, n_f\, n_p\ \bar{X}^2$
Year (y)	n_y - 1	$\bar{X}_y = \frac{1}{n_s n_f n_p} \sum_s \sum_f \sum_p X_{syfp}$	$n_s\, n_f\, n_p\, \Sigma\, \bar{X}_y^2$ - $n_s\, n_y\, n_f\, n_p\ \bar{X}^2$
School x Year	$(n_s - 1)(n_y - 1)$	$\bar{X}_{sy} = \frac{1}{n_f n_p} \sum_f \sum_p X_{syfp}$	$n_f\, n_p\, \Sigma\Sigma\, \bar{X}_{sy}^2$ - $n_f\, n_y\, n_p\, \Sigma\, \bar{X}_s^2$ - $n_s\, n_f\, n_p\, \Sigma\, \bar{X}_y^2 + n_s\, n_y\, n_f\, n_p\ \bar{X}^2$
Form:Year (f:y)	$n_y(n_f - 1)$	$\bar{X}_{f:y} = \frac{1}{n_s n_p} \sum_s \sum_p X_{syfp}$	$n_s\, n_p\, \Sigma\Sigma\, \bar{X}_{yf}^2$ - $n_s\, n_f\, n_p\, \Sigma\, \bar{X}_y^2$
School x Form : Year (sf:y)	$n_y(n_s - 1)(n_f - 1)$	$\bar{X}_{sf:y} = \frac{1}{n_p} \sum_p X_{syfp}$	$n_p\, \Sigma\Sigma\Sigma\, \bar{X}_{syf}^2$ - $n_f\, n_p\, \Sigma\Sigma\, \bar{X}_{sy}^2$ - $n_s\, n_p\, \Sigma\Sigma\, \bar{X}_{yf}^2 + n_s\, n_f\, n_p\ \bar{X}_y^2$
Pupil: School Year Form (p:sfy)	$n_y n_s n_f (n_p - 1)$	na	$\Sigma\Sigma\Sigma\Sigma\, X_{psyf}^2$ - $n_p\, \Sigma\Sigma\Sigma\, \bar{X}_{syf}^2$
Total	$n_s\, n_y\, n_f\, n_p$-1	$\bar{X} = \frac{1}{n_s n_y n_f n_p} \sum_s \sum_y \sum_f \sum_p X_{syfp}$	$\Sigma\Sigma\Sigma\Sigma\, X_{psyf}^2$ - $n_s\, n_y\, n_f\, n_p\, \bar{X}^2$

Table A-2
Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – G-Study Estimates

Effect (α)	Estimated σ^2 –Random Effects Model	Estimated $\sigma^2(\alpha\|M)$ -- Mixed Models (N = Universe size): Basic Mixed Model	Year Fixed
School (s)	$\frac{[MS(s) - MS(sy)]}{n_y n_f n_p}$	$\hat{\sigma}^2_s + \frac{\hat{\sigma}^2_{sy}}{N_y} + \frac{\hat{\sigma}^2_{sf:y}}{N_f N_y} + \frac{\hat{\sigma}^2_{p:f:sy}}{N_f N_y N_p}$	$\hat{\sigma}^2_s + \frac{\hat{\sigma}^2_{sy}}{N_y}$
Year (y)	$\frac{[MS(y) - MS(sy) - MS(fy) + MS(sfy)]}{n_s n_f n_p}$	$\hat{\sigma}^2_y + \frac{\hat{\sigma}^2_{sy}}{N_s} + \frac{\hat{\sigma}^2_{f:y}}{N_f} + \frac{\hat{\sigma}^2_{sf:y}}{N_s N_f} + \frac{\hat{\sigma}^2_{p:f:sy}}{N_s N_f N_p}$	$\hat{\sigma}^2_y$
School x Year	$\frac{[MS(sy) - MS(sfy)]}{n_f\, n_p}$	$\hat{\sigma}^2_{sy} + \frac{\hat{\sigma}^2_{sf:y}}{N_f} + \frac{\hat{\sigma}^2_{p:f:sy}}{N_f N_p}$	$\hat{\sigma}^2_{sy}$
Form:Year (f:y)	$\frac{[MS(fy) - MS(sfy)]}{n_s\, n_p}$	$\hat{\sigma}^2_{f:y} + \frac{\hat{\sigma}^2_{sf:y}}{N_s} + \frac{\hat{\sigma}^2_{p:f:sy}}{N_s N_p}$	$\hat{\sigma}^2_{f:y}$
School x Form : Year (sf:y)	$\frac{[MS(sfy) - MS(syfp)]}{n_p}$	$\hat{\sigma}^2_{f:sy} + \frac{\hat{\sigma}^2_{p:f:sy}}{N_p}$	$\hat{\sigma}^2_{f:sy}$
Pupil: School Year Form (p:sfy)	MS(syfp)	$\hat{\sigma}^2_{p:f:sy}$	$\hat{\sigma}^2_{p:f:sy}$

Table A-3
Estimating Variance Components for Pupil: School Year Form Generalizability Theory Design – D-study Estimates

Effect (α)	D-study error component	Use term in: Absolute error estimate	Relative error estimate
School (s)	$\hat{\sigma}^2_s + \frac{\hat{\sigma}^2_{sy}}{N_y}$		
Year (y)	$[\hat{\sigma}^2_y \;/ N_y]\;[1 - \frac{n_y}{N_y}] = \mathbf{0}$	(X)	
School x Year	$[\hat{\sigma}^2_{sy} \;/N_y] \times [1 - \frac{n_y}{N_y}] = \mathbf{0}$	(X)	(X)
Form:Year (f:y)	$\hat{\sigma}^2_{f:y} \;/ N_y N_f$	X	
School x Form : Year (sf:y)	$\hat{\sigma}^2_{f:sy} \;/ N_y N_f$	X	X
Pupil: School Year Form (p:sfy)	$\hat{\sigma}^2_{p:f:sy} / N_y N_f\, n_p$	X	X

Note that current literature is mixed on whether pupils should be considered fixed, random, or sampled from a fixed domain (Cronbach, Linn, Brennan, & Haertel, 1997; Hambleton, Jaeger, Koretz, Linn, Millman, & Phillips, 1996; Yen, 1997). Persistent criticisms of Kentucky's accountability model that cohort-to-cohort variation in student proficiency is unfair (Hoffman, 1998) makes treating students as fixed unwise. Yen uses two different approaches, one for which students are random, and a second for which students are treated as samples of a finite domain with that domain being defined as the total school population from which the tested students are taken. Yen's second approach does not fit Kentucky's two-year cycle very well, particularly since we know that transience among students is perceived to be a significant issue for some districts (Thacker, Koger, Hoffman, and Koger, 2000) and is indeed related to school scores (Medsker, 1998). Therefore, we have chosen to treat students as random, i.e., sampled from an infinite universe. (Note also that in Yen's second approach, she adds a term for measurement error at the person level. That term is mathematically eliminated when students are treated as random.)

Yen (1997) also discussed potential modification to the forms by schools interaction given that forms are intended to target slightly different content. She concludes that since there is no way to directly test differences in targets (forms and students are confounded), the straightforward approach, as presented in Tables A2 – A4, is more acceptable with a caveat that it may overestimate standard error.

Absolute and relative error

Generalizability theory considers two kinds of error: absolute and relative. Absolute error is appropriate to consider when the objects of measure (schools in our case) are being assessed against a standard that generalizes beyond any of the particular instances of the various facets of measurement (e.g., different forms, different years, different pupils). Relative error, on the other hand, is appropriate when schools are being compared to each other and have been subject to the same measurement processes (same forms, same years). Table A-3 indicates which variance components enter each type of error estimate. With years treated as fixed, three error components (form within year, school by form within year, and pupil within form within school by form) are summed to estimate absolute error. Only the later two components (school by form within year, and pupil within form within school by form) are summed to estimate error variance for the relative model. Because schools are being assessed against a standard, rather than by relative standing among other schools, absolute error is the appropriate estimate to use in computing CATS classification accuracy.

Special Considerations for Writing Assessments

Each student completes one on-demand writing prompt, and it is chosen by the student from a pair of alternatives. Six pairs of writing prompts constitute six forms for on-demand writing. From past analysis (Hoffman, Koger, & Awbrey,1997), we know that means for different writing prompts vary greatly for prompts within a form as well as for prompts from different forms. The variation in means leads to the conclusion that each prompt should be treated as a separate "form" using the same Generalizability analysis design described above. As far as the self-selection factor is concerned, we see no option other than considering it one of the random factors affecting prompt (i.e., item) sampling.

Portfolios, however, are (in theory[4]) unique to each individual student. "Forms" as a theoretical facet for portfolios is confounded with students.[5] Therefore, school-level error variance for portfolios will be assessed using a Generalizability design similar to the one presented above, but without form as a facet. That is, pupils are nested within the intersection of schools and years. Formulas for this three facet (pupils: schools x years) are available in Brennan (1981), designated as i:(p x h) in his notation.

CTBS/5

CTBS/5 scores also do not include separate forms at any one of the grade levels in which it is administered. Therefore the same Generalizability model applied to writing portfolios is applied to CTBS/5 scores.

[4] Some schools do tend to structure common activities and present selected topics for students to create portfolio entries.

[5] Again, this is an oversimplication. Anecdotally, some schools reportedly have been doing a better job than others of structuring portfolio activities that facilitate higher quality writing. "Item sampling," therefore, may be confounded with schools. In this unusual case, schools become both the object of measurement and an instrument, or facet, of measurement.

Table A-4
Variance Components for Each Grade/Subject By School Size Configuration for Baseline 1999-2000

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
3	ct	lg	66	96	2	.	11.935	11.935	281.277	0.958	0.958
3	ct	md	35	60	2	.	18.568	18.568	406.480	0.954	0.954
3	ct	sm	49	24	2	.	48.407	48.407	275.457	0.824	0.824
4	rd	lg	36	16	2	6	6.208	5.995	101.721	0.939	0.941
4	rd	md	55	10	2	6	8.106	8.028	140.524	0.942	0.943
4	rd	sm	44	4	2	6	22.325	21.798	75.395	0.704	0.711
4	sc	lg	36	16	2	6	6.119	6.119	110.375	0.945	0.945
4	sc	md	55	10	2	6	7.821	7.821	182.917	0.957	0.957
4	sc	sm	44	4	2	6	18.186	17.839	108.250	0.832	0.835
4	wod	lg	35	16	2	6	5.651	5.512	44.072	0.872	0.875
4	wod	md	54	10	2	6	7.972	7.896	52.788	0.849	0.850
4	wod	sm	42	4	2	6	15.894	15.867	47.132	0.663	0.663
4	wp	lg	54	96	2	.	4.048	4.048	147.104	0.972	0.972
4	wp	md	29	60	2	.	6.090	6.090	199.888	0.970	0.970
4	wp	sm	51	24	2	.	17.683	17.683	227.601	0.922	0.922
5	ah	lg	28	8	2	12	8.067	7.939	143.255	0.944	0.945
5	ah	md	39	5	2	12	10.796	10.459	119.436	0.910	0.912
5	ah	sm	28	2	2	12	22.270	22.175	85.604	0.740	0.741
5	ma	lg	33	16	2	6	7.364	7.186	200.391	0.963	0.964
5	ma	md	57	10	2	6	9.426	9.426	178.516	0.947	0.947
5	ma	sm	39	4	2	6	22.213	22.213	145.874	0.848	0.848
5	pl	lg	28	8	2	12	8.868	8.632	142.296	0.938	0.939
5	pl	md	38	5	2	12	12.913	12.737	131.288	0.902	0.903
5	pl	sm	28	2	2	12	31.440	31.440	156.133	0.799	0.799
5	ss	lg	32	16	2	6	8.144	8.144	229.568	0.965	0.965
5	ss	md	57	10	2	6	12.491	12.312	199.534	0.937	0.938
5	ss	sm	39	4	2	6	27.197	26.125	199.494	0.864	0.869
6	ct	lg	36	180	2	.	6.494	6.494	159.455	0.959	0.959
6	ct	md	42	60	2	.	18.344	18.344	335.471	0.945	0.945
6	ct	sm	41	24	2	.	49.311	49.311	181.653	0.729	0.729
7	rd	lg	41	40	2	6	2.293	2.205	122.577	0.981	0.982
7	rd	md	22	20	2	6	4.428	4.230	49.878	0.911	0.915
7	rd	sm	28	6	2	6	12.799	12.799	107.816	0.881	0.881
7	sc	lg	41	40	2	6	3.591	3.571	173.255	0.979	0.979
7	sc	md	22	20	2	6	7.215	7.215	80.072	0.910	0.910
7	sc	sm	28	6	2	6	15.238	14.478	187.607	0.919	0.923

Table A-4
Variance Components for Each Grade/Subject By School Size Configuration for Baseline 1999-2000

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
7	wod	lg	41	40	2	6	2.510	2.260	64.101	0.961	0.965
7	wod	md	22	20	2	6	4.330	4.249	30.428	0.858	0.860
7	wod	sm	27	6	2	6	11.789	11.789	75.778	0.844	0.844
7	wp	lg	48	240	2	.	1.733	1.733	148.413	0.988	0.988
7	wp	md	27	120	2	.	3.700	3.700	69.190	0.947	0.947
7	wp	sm	36	36	2	.	12.672	12.672	120.415	0.895	0.895
8	ah	lg	29	20	2	12	3.241	3.208	126.937	0.974	0.975
8	ah	md	26	10	2	12	6.147	6.061	106.441	0.942	0.943
8	ah	sm	21	3	2	12	17.900	17.649	270.439	0.934	0.935
8	ma	lg	40	40	2	6	2.484	2.446	128.201	0.981	0.981
8	ma	md	27	20	2	6	4.868	4.781	79.019	0.938	0.939
8	ma	sm	26	6	2	6	13.543	13.543	345.025	0.961	0.961
8	pl	lg	30	20	2	12	3.398	3.356	108.562	0.969	0.969
8	pl	md	26	10	2	12	7.395	7.356	104.654	0.929	0.930
8	pl	sm	20	3	2	12	22.297	22.297	257.481	0.913	0.913
8	ss	lg	41	40	2	6	3.185	3.185	108.854	0.971	0.971
8	ss	md	27	20	2	6	5.375	5.191	109.991	0.951	0.953
8	ss	sm	26	6	2	6	12.817	12.455	273.806	0.953	0.955
9	ct	lg	46	312	2	.	4.143	4.143	327.514	0.987	0.987
9	ct	md	36	168	2	.	7.733	7.733	236.606	0.967	0.967
9	ct	sm	36	24	2	.	53.091	53.091	305.827	0.826	0.826
10	pl	lg	47	20	2	12	3.276	3.190	106.937	0.969	0.970
10	pl	md	29	14	2	12	5.655	5.495	65.694	0.914	0.916
10	pl	sm	26	5	2	12	12.844	12.844	65.829	0.805	0.805
10	rd	lg	56	40	2	6	2.392	2.338	102.136	0.977	0.977
10	rd	md	39	28	2	6	3.839	3.748	61.919	0.938	0.939
10	rd	sm	29	10	2	6	8.099	8.099	65.020	0.875	0.875
11	ah	lg	35	20	2	12	3.443	3.365	161.583	0.979	0.979
11	ah	md	24	14	2	12	4.278	4.218	101.996	0.958	0.959
11	ah	sm	34	5	2	12	10.347	10.321	102.731	0.899	0.900
11	ma	lg	40	40	2	6	3.068	2.840	168.993	0.982	0.983
11	ma	md	27	28	2	6	3.814	3.750	172.664	0.978	0.978
11	ma	sm	38	10	2	6	9.492	9.249	102.219	0.907	0.910
11	sc	lg	40	40	2	6	2.923	2.754	96.554	0.970	0.971
11	sc	md	27	28	2	6	3.194	2.849	78.908	0.960	0.964
11	sc	sm	38	10	2	6	7.591	7.519	74.248	0.898	0.899
11	ss	lg	40	40	2	6	2.352	2.310	140.559	0.983	0.984
11	ss	md	27	28	2	6	2.871	2.753	99.381	0.971	0.972

Table A-4
Variance Components for Each Grade/Subject By School Size Configuration for Baseline 1999-2000

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
11	ss	sm	38	10	2	6	7.874	7.874	75.181	0.895	0.895
12	wod	lg	29	40	2	6	1.673	1.606	21.860	0.923	0.927
12	wod	md	29	28	2	6	2.853	2.636	37.943	0.925	0.931
12	wod	sm	29	10	2	6	6.263	6.263	40.971	0.847	0.847
12	wp	lg	36	240	2	.	1.991	1.991	61.669	0.968	0.968
12	wp	md	50	168	2	.	3.002	3.002	82.675	0.964	0.964
12	wp	sm	42	60	2	.	7.959	7.959	92.523	0.914	0.914

Table A-5
Variance Components for Each Grade/Subject By School Size Configuration for End-of-Cycle 2000-2002

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
3	ct	lg	52	96	2	.	11.301	11.301	179.396	0.937	0.937
3	ct	md	34	60	2	.	17.775	17.775	178.291	0.900	0.900
3	ct	sm	43	24	2	.	45.260	45.260	338.520	0.866	0.866
4	rd	lg	44	16	2	6	4.657	4.607	132.125	0.965	0.965
4	rd	md	23	10	2	6	9.382	9.359	122.894	0.924	0.924
4	rd	sm	38	4	2	6	20.121	19.962	97.720	0.794	0.796
4	sc	lg	44	16	2	6	5.023	5.000	139.087	0.964	0.964
4	sc	md	23	10	2	6	8.737	8.695	135.448	0.936	0.936
4	sc	sm	38	4	2	6	17.589	17.575	124.095	0.858	0.858
4	wo	lg	42	16	2	6	5.765	5.645	62.046	0.907	0.909
4	wo	md	24	10	2	6	7.672	7.441	70.553	0.891	0.895
4	wo	sm	38	4	2	6	15.552	15.457	46.134	0.663	0.665
4	wp	lg	67	96	2	.	3.748	3.748	137.328	0.973	0.973
4	wp	md	35	60	2	.	5.895	5.895	171.089	0.966	0.966
4	wp	sm	44	24	2	.	16.507	16.507	234.587	0.930	0.930
5	ah	lg	30	8	2	12	7.067	6.877	62.582	0.887	0.890
5	ah	md	11	5	2	12	9.976	9.507	86.183	0.884	0.890
5	ah	sm	27	2	2	12	20.184	20.184	167.725	0.880	0.880
5	ma	lg	43	16	2	6	7.795	7.670	155.500	0.950	0.951
5	ma	md	26	10	2	6	9.994	9.552	142.124	0.930	0.933
5	ma	sm	37	4	2	6	25.849	25.849	120.533	0.786	0.786
5	pl	lg	30	8	2	12	8.549	8.549	102.587	0.917	0.917
5	pl	md	11	5	2	12	13.614	13.014	87.335	0.844	0.851
5	pl	sm	27	2	2	12	28.768	28.561	156.052	0.816	0.817
5	ss	lg	43	16	2	6	8.791	8.631	151.189	0.942	0.943
5	ss	md	26	10	2	6	13.448	13.187	108.136	0.876	0.878
5	ss	sm	37	4	2	6	25.633	25.633	194.404	0.868	0.868
6	ct	lg	32	180	2	.	6.651	6.651	122.636	0.946	0.946
6	ct	md	37	60	2	.	18.372	18.372	211.300	0.913	0.913
6	ct	sm	28	24	2	.	47.368	47.368	263.054	0.820	0.820
7	rd	lg	44	40	2	6	2.064	2.064	107.839	0.981	0.981
7	rd	md	30	20	2	6	3.729	3.728	56.470	0.934	0.934
7	rd	sm	23	6	2	6	13.805	13.805	144.395	0.904	0.904
7	sc	lg	44	40	2	6	3.308	3.296	178.371	0.981	0.982
7	sc	md	30	20	2	6	5.882	5.882	110.433	0.947	0.947
7	sc	sm	23	6	2	6	22.134	22.134	228.742	0.903	0.903

Table A-5
Variance Components for Each Grade/Subject By School Size Configuration for End-of-Cycle 2000-2002

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
7	wo	lg	46	40	2	6	3.174	2.590	60.799	0.948	0.957
7	wo	md	30	20	2	6	4.986	4.271	43.439	0.885	0.902
7	wo	sm	24	6	2	6	13.439	13.055	117.444	0.886	0.889
7	wp	lg	50	240	2	.	1.883	1.883	137.526	0.986	0.986
7	wp	md	34	120	2	.	4.145	4.145	113.888	0.964	0.964
7	wp	sm	30	36	2	.	14.465	14.465	157.291	0.908	0.908
8	ah	lg	32	20	2	12	3.041	2.855	85.091	0.964	0.966
8	ah	md	20	10	2	12	5.754	5.626	107.069	0.946	0.947
8	ah	sm	12	3	2	12	16.491	16.491	335.248	0.951	0.951
8	ma	lg	36	40	2	6	2.512	2.512	103.781	0.976	0.976
8	ma	md	21	20	2	6	4.778	4.743	63.363	0.925	0.925
8	ma	sm	18	6	2	6	14.543	14.506	319.037	0.954	0.955
8	pl	lg	31	20	2	12	3.337	3.106	65.470	0.949	0.953
8	pl	md	20	10	2	12	6.309	6.229	96.428	0.935	0.935
8	pl	sm	12	3	2	12	20.069	19.767	281.090	0.929	0.930
8	ss	lg	36	40	2	6	2.837	2.696	77.948	0.964	0.965
8	ss	md	21	20	2	6	5.919	5.482	95.055	0.938	0.942
8	ss	sm	18	6	2	6	15.021	14.885	189.123	0.921	0.921
9	ct	lg	65	240	2	.	5.520	5.520	174.528	0.968	0.968
9	ct	md	45	168	2	.	7.966	7.966	163.819	0.951	0.951
9	ct	sm	37	42	2	.	31.002	31.002	198.882	0.844	0.844
10	pl	lg	53	20	2	12	3.234	3.158	83.684	0.961	0.962
10	pl	md	21	14	2	12	5.403	5.149	69.278	0.922	0.926
10	pl	sm	34	5	2	12	12.247	12.066	94.772	0.871	0.873
10	rd	lg	58	40	2	6	2.420	2.269	102.027	0.976	0.978
10	rd	md	25	28	2	6	4.736	4.040	62.396	0.924	0.935
10	rd	sm	37	10	2	6	8.849	8.365	127.656	0.931	0.934
11	ah	lg	25	20	2	12	3.447	3.277	127.186	0.973	0.974
11	ah	md	25	14	2	12	4.772	4.626	103.049	0.954	0.955
11	ah	sm	26	5	2	12	11.973	11.973	117.113	0.898	0.898
11	ma	lg	33	40	2	6	3.215	3.187	152.365	0.979	0.979
11	ma	md	33	28	2	6	3.790	3.790	126.168	0.970	0.970
11	ma	sm	32	10	2	6	9.946	9.946	169.573	0.941	0.941
11	sc	lg	33	40	2	6	2.544	2.484	69.708	0.964	0.964
11	sc	md	33	28	2	6	3.022	2.979	69.404	0.956	0.957
11	sc	sm	32	10	2	6	8.709	8.709	97.455	0.911	0.911
11	ss	lg	33	40	2	6	3.050	3.050	119.734	0.975	0.975
11	ss	md	33	28	2	6	3.656	3.627	81.284	0.955	0.955

Table A-5
Variance Components for Each Grade/Subject By School Size Configuration for End-of-Cycle 2000-2002

rd = Reading sc = Science wo = Writing Prompt wp = Writing Portfolio ah = Arts & Humanities ma = Mathematics pl = PL/VS ss = Social Studies	Lg = Large School Md = Medium School Sm = Small School	NS = Number of Schools NP = Number of Pupils NF = Number of Forms NY = Number of Years	Ab, Err = Absolute Error Variance Rel. Error = Relative Error Variance Tot Var. = Total Variance	Ab. Gen. = Absolute Generalizability Rel. Gen. = Relative Generalizability

Grade	Subject	School Size	NS	NP	NY	NF	Absol. Err.	Rel. Err.	Total Var.	Absol. Gen.	Rel. Gen.
11	ss	sm	32	10	2	6	10.804	10.804	147.130	0.927	0.927
12	wo	lg	32	40	2	6	1.553	1.426	18.940	0.918	0.925
12	wo	md	30	28	2	6	2.572	2.252	22.278	0.885	0.899
12	wo	sm	36	10	2	6	6.056	6.025	40.006	0.849	0.849
12	wp	lg	36	240	2	.	2.056	2.056	44.970	0.954	0.954
12	wp	md	45	168	2	.	3.073	3.073	62.765	0.951	0.951
12	wp	sm	43	60	2	.	8.590	8.590	105.783	0.919	0.919

Weights Used in Calculating Accountability Index Score and Accountability Index SEMs

Table A-6 Weight Used in Calculating Accountability Index Score and Accountability Index SEMs

Grade	Subject	WK_5	WK_6	WK_8	WK_12	W4_5	W4_6	W4_8	W6_8	W6_12	W7_8	W7_9	W7_12	W9_12	W10_12
03	ct	.050000	.025000	.025000	.016667										
04	rd	.190000	.190000	.095000	.063333	.200000	.190000	.100000							
04	sc	.142500	.142500	.071250	.047500	.150000	.142500	.075000							
04	wod	.028500	.028500	.014250	.009500	.030000	.028500	.015000							
04	wp	.114000	.114000	.057000	.038000	.120000	.114000	.060000							
05	ah	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	ma	.190000	.190000	.095000	.063333	.200000	.190000	.100000							
05	na	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	pl	.047500	.047500	.023750	.015833	.050000	.047500	.025000							
05	ss	.142500	.142500	.071250	.047500	.150000	.142500	.075000							
06	ct		.025000	.025000	.016667		.050000	.025000	.050000	.025000					
07	rd			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
07	sc			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
07	wod			.014250	.009500			.014250	.028500	.014250	.030000	.028500	.015000		
07	wp			.057000	.038000			.057000	.114000	.057000	.120000	.114000	.060000		
08	ah			.035625	.023750			.035625	.071250	.035625	.075000	.071250	.037500		
08	ma			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
08	na			.047500	.031667			.047500	.095000	.047500	.100000	.095000	.050000		
08	pl			.035625	.023750			.035625	.071250	.035625	.075000	.071250	.037500		
08	ss			.071250	.047500			.071250	.142500	.071250	.150000	.142500	.075000		
09	ct				.016667					.025000		.050000	.025000	.050000	
10	pl				.023750					.035625			.035625	.071250	.075000
10	rd				.047500					.071250			.071250	.142500	.150000
11	ah				.023750					.035625			.035625	.071250	.075000
11	ma				.047500					.071250			.071250	.142500	.150000
11	sc				.047500					.071250			.071250	.142500	.150000
11	ss				.047500					.071250			.071250	.142500	.150000
12	na				.031667					.047500			.047500	.095000	.100000
12	wod				.009500					.014250			.014250	.028500	.030000
12	wp				.038000					.057000			.057000	.114000	.120000

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